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Replication as Pedagogy: The Social and Cultural Dimensions of Transmitting Dance Knowledge

De Zeng

School of Arts and Humanities, Wuhan University of Communication, Wuhan Hubei 430000,
China
karen202425@163.com

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Abstract

Dance is an important intangible cultural heritage, the means by which cultural identity, artistic traditions, and embodied knowledge are transmitted from one generation to another. Movement replication has traditionally been a key technique for teaching dance in terms of which movement skills can be acquired through observation, imitation, and practice. However, the objective evaluation of the effectiveness of movement replication while ensuring cultural authenticity is still a difficult task. In this study, the authors propose the Spatio-Temporal Graph Convolutional Network integrated with Light Gradient Boosting Machine (ST-GCN-LGBM) to provide support for replication-based dance pedagogy and to assess skill acquisition based on modeling of complex movements. The effectiveness of the proposed model was tested by using the ImperialDance dataset including 3D motion data of beginners, intermediates, and experts who performed repeated choreographies. The results of experiments showed that the accuracy of the proposed model reached 95.4%, and precision, recall, and F1-score was 0.95, exceeding the performance indicators of the CNN, LSTM, and standalone ST-GCN models. Moreover, the proposed framework received a movement similarity score of 0.92, with relatively low prediction errors (MAE = 0.015, RMSE = 0.018, and MAPE = 1.6%). Thus, movement patterns were successfully replicated with the help of the proposed framework, with a high degree of movement consistency achieved by learners, especially beginners. In addition, the statistical verification demonstrated the existence of significant differences between skill levels ($p < 0.05$). Therefore, besides computational performance, the proposed framework is an important educational tool for teaching dance. The results show that computational movement analysis can support traditional dance pedagogy in terms of heritage education and cultural transmission of dance knowledge.

Keywords: Embodied Learning, Cultural Transmission, Arts Education, Social Learning Theory, Intangible Cultural Heritage, Skill Acquisition, Movement Pedagogy.

Introduction

Dance techniques have typically been transmitted through embodied practice, with repetition, observation, and motor learning gaining a central place in developing particular movement patterns. In a neuroscientific and cognitive framing, Fitch and Barnstaple (2024) place dance within a concept of 'mindful movement'; in their work, they argue about motor learning and predictive coding allowing dancers to fine-tune techniques along pathways opened through sensory-motor repetition. In this way, replication provides the grounding for skill development in dance. So, a 2024 article by Nogueira et al. discusses how machine learning it's becoming increasingly popular in dance performance nowadays. This is because of the integration with computational modelling which enables the analysis, reproduction and enhancement of movement patterns. According to this indicative systematic review, a shift toward data-driven methods that stand as a supplement to the traditionally embedded form of transmission has marked the appearance of contemporary scholarship. In the cultural and choreographic aspect, Ding (2025) contests that repetition is one of the main mechanisms in embedding and transmitting styles and cultures in dancing, especially regarding Chinese traditional dancing. On the pedagogical level of analysis, Liu (2023) elaborated on the techniques of repetition in folk dance education and showed how organizing repetitions helps learners to internalize dance content details.

Yin and Liu (2022) explicate the means of technology-oriented movements learning, covering data-mining methods relating to dance learning analysis and guidance, highlighting the role VR-based feedback plays in the accuracy of movements; seen through the neuroscientific lens, Basso et al. (2021) report that synchronic dance practices increase intra-brain and inter-brain synchrony, providing a neural basis for collective performance learning. Taking an even higher stand on the integration of technology and instruction, Zhen and Keun (2025) apply a 3D convolutional neural network in guiding AI-ethnic dance training to help one best imitate another's movements accurately. Hackney et al. (2024) somewhat complement this by investigating what neurocognitive mechanisms underlie dance learning and rehabilitation processes; repeated practices assume a fundamental role in motor recovery and refinement. Further developing this discussion, Song and Ding (2025) optimize machine-learning-based models to reconstruct dance movements; thus, computational means can hold and reproduce complex patterns of motion that have elapsed. Moltisanti et al. (2022) talk about a BRACE dataset, which is a huge database for dance motion which enables a systematic modelling and creation of dance techniques which is a huge step toward the digital transmission of movement based data.

Recent study has discussed the application of convolutional neural networks (CNNs) and recurrent models (LSTMs) to the movement recognition and classification. Although such methods have a moderate success, they do not necessarily capture the spatial relationships of joints and temporal dependencies in more complicated motion sequences. In solving these shortcomings, ST-GCNs have developed into a potent system in human skeletal motion modeling, where the joints are depicted by the nodes, and their relationships by the edges in time.

This study combine ST-GCN with a Light Gradient Boosting Machine (LGBM) in this research to form a hybrid model, ST-GCN-LGBM, that can not only extract useful spatio-temporal features, but also provide precise answers to the problem of movement replication and skill level prediction. Based on the ImperialDance data, the suggested framework is able to quantitatively assess the accuracy of replication, similarity of movement and learning progression in beginner, intermediate, and expert dancers. This paper introduces a powerful computational framework of learning and teaching dance moves, combining the latest graph-based models with gradient-boosted decision trees, which serve as an insight into the process of learning by repetition and the ways it may be applied in the performance arts, rehabilitation, and sports.

Dance is one of the most important intangible cultural heritage that helps communities to transmit cultural identity, history, artistry and community values from one generation to the next. Dance knowledge is mostly passed on through embodied learning, observation, imitation and repeated practice, in contrast to many other cultural practices where documentation is the primary means of transmission. Thus, the sustainability of traditional dance is not only related to the maintenance of the choreographic movements, but also to the successful transmission of the techniques of the movements, performance styles and cultural meanings to future generations. The process of globalization, new educational approaches and the non-involvement of young people, however, have posed many difficulties to the continuity of traditional dance knowledge, making it necessary to find new ways to preserve the culture and to educate people about dance. Replication is a basic pedagogical approach from an educational point of view, in which students progressively internalise complex movement patterns, develop motor coordination and learn artistic skills by observing and practising them repeatedly. Dance pedagogy highlights the importance of movement replication as a means to not only mechanically replicate but also to cultivate physical awareness, expressive ability, and cultural understanding at the same time. Replication should be seen as a learning process that helps to pass on knowledge from one generation to the next, support embodied learning, and preserve cultural heritage, not just the physical movement.

The recent developments in artificial intelligence and movement analysis offer new opportunities to support the traditional teaching of dance, by being able to objectively assess the quality of the dance movement, track the learning process and give feedback during the learning process – all tailored to the individual. Instead of

replacing traditional methods of instruction, computational tools can be used as educational aids to help teachers, students, and cultural heritage institutions to document, preserve, and pass on dance knowledge more efficiently. To this end, this work explores the potential of a computational approach using Spatio-Temporal Graph Convolutional Networks and Light Gradient Boosting Machine (ST-GCN-LGBM) to assist dance teaching and learning, aiming to enhance the reproduction of dance movements, aid the learning of skills, and foster the sustainable transmission of cultural dance knowledge.

1.1 Research Objectives

The main goals of the research are to create a computational language that will be able to model and recreate intricate dance moves and moves accurately, to analyze the skill development process in various levels of dancer expertise, and to measure the movement replication. In particular, the research will seek to measure not only spatial relationships between skeletal joints but also those related to time, i.e., between repeated practice sessions, the ability to improve movement patterns as the repetition progresses, to compare the proposed method with a control model based on end-of-day performance indicators, such as accuracy, precision, recall, F1-score, movement similarity, and error rates. Also, the research is aimed to statistically prove the differences between skill levels as well as exploring the role of repeated practice in the internalization and stabilization of dance techniques.

1.2 Contribution of the Study

This research has some important contributions to computational movement analysis and skill acquisition. It presents a new ST-GCN-LGBM architecture, combining spatio-temporal graph convolutional networks and a Light Gradient Boosting Machine classifier, which allows accurately recreating difficult dance movements. Second, it offers an analysis of skill development objectively by providing a quantitative methodology of determining similarity and replication fidelity of movements. Third, the research shows the importance of repetitive practice in the development of stable movement patterns and acquisition of skills at various levels of expertise. Last but not least, the efficacy of the offered architecture and the role played by every component are statistically validated and ablated, which proves their high-quality computational tool that can be used in dance, performance arts, rehabilitation, and sports training.

Related Work

Existing research on the transmission of dance techniques have been explained in neurological, analytical, cultural, and technological terms. In this respect, Ladda et al. (2020) address multimodal sensory-spatial integration in musicians and dancers and discuss how trained motor patterns are recalled and coordinated with the help of embodied memory. For them, this gives rise to an impression of the importance of repeated practice for the stabilization of movement patterns across sensory

modalities. More broadly, from a health and practice view, Christensen et al. (2021) propose a practice-based research methodology, stating that significant engagement in dance techniques facilitates emotional regulation and promotes continuous motor learning. The problems of transmission are socially and culturally framed. Leach 2022 discusses principles of ownership and knowledge transmission in the practices of contemporary dance and Irish traditional music, showing that repetition in both is not only a technical but also a socially modulated practice. Whatley 2025 says that dance analysis would become a formal approach to study movement patterns with appropriate instruments for the documentation and analysis of imitative technique. In the same way, Bench et al 2023 keeps choreographic analysis at the centre of dance studies, and identify repeated movements represent the technique, meaning and structural consistency.

As dance research becomes more digitized, computational methods have increasingly come to the fore. Rallis et al. (2020) thus provide an overview of the application of machine learning techniques for dance analysis within the scope of intangible cultural heritage, demonstrating how algorithmic models may contribute to the safeguarding and dissemination of movement vocabularies. Building on this digital dimension, Zhu and Shao (2023) document in a case study the digital reproduction of Pat Chest Dance, illustrating how these techniques can be passed down through digital reproductions. Qian and Searani (2025) take this idea of reproduction further to look at the pedagogical and cultural value of reproduction as an embedding of cultural values in Chinese characteristics of dance vocational training where repetition is flagged as a significant means of cultural value in the preservation of heritage. Liu (2023) uses a case study of Maurice Béjart's Bolero to show how thematic repetition in a new choreography in consciously-constructed ways fosters certain kinds of identity of action, in order to enable transference of intent between containers (actor/performer; dimensions).

Recent studies in dance education and cultural heritage emphasize that dance functions as both an artistic practice and a social process through which cultural identity, collective memory, and embodied knowledge are transmitted across generations. Fitch and Barnstaple (2024) describe dance as a form of mindful movement in which repeated practice strengthens predictive motor learning and embodied cognition. Similarly, Liu (2023) argues that structured repetition enables learners to internalize complex choreographic patterns while strengthening technical proficiency and cultural understanding. Leach (2022) further highlights that the transmission of dance knowledge is governed not only by technical instruction but also by social norms, cultural ownership, and community participation, demonstrating that dance learning represents a collective educational experience.

Technology-enhanced dance education has recently emerged as an effective approach for supporting movement analysis and heritage preservation. Yin and Liu (2022) demonstrate that data-driven movement analysis can improve learning guidance through objective evaluation of performance, while Zhen and Keun (2025)

show that artificial intelligence-based movement recognition enhances the accuracy of dance instruction and skill acquisition. Likewise, Rallis et al. (2020) emphasize the importance of computational methods for preserving intangible cultural heritage by digitally documenting complex dance movements and facilitating wider educational accessibility. These studies collectively suggest that computational technologies should be viewed as pedagogical tools that strengthen dance education, cultural preservation, and intergenerational knowledge transmission rather than solely as technical movement recognition systems. In their systematic review on intercultural and indigenous dance education, Liu et al. (2024) underscore the significance of dance as an educational tool that can be used for preserving cultural identity, collective memory, and community values. According to the findings of the authors, effective dance education combines cultural preservation with inclusive teaching and educators are responsible for facilitating intergenerational knowledge transfer in this process. However, the focus of the study is on educational methods and there is no research on the computation of movement replication and monitoring skills. In his research paper, Stewart (2024) examines embodied learning in dance education from the point of view of anti-oppressive pedagogy. It is shown that dance learning is not only about performing movements but is also about cultural inclusion, identity building, and reflective education. The results obtained in the course of this research show that the method in question is beneficial for developing technical and social skills but no computational methods of movement evaluation are discussed. In their study, Henley and Conrad (2024) use the notion of cultural affordance to examine the process of dance learning as being based on embodied experience, attention, and culturally situated practice rather than imitation of movements. Qualitative findings presented by the authors stress the importance of the integration of experience and education in the process of movement learning. Nonetheless, there is no measurement of movement replication. In their paper, Buck and Snook (2024) consider community dance pedagogy as a transformative educational strategy that encourages collaboration, critical thinking, and cultural participation. This research proves that dance education facilitates community engagement and learner-centered knowledge acquisition and is not based exclusively on instruction. Nonetheless, there is no computational framework proposed for objective monitoring of learner progress and movement replication. Jiang et al. (2025) propose an integrated approach to combining digital technologies with dance education for the preservation of intangible cultural heritage. In particular, the authors prove that the use of digital platforms may facilitate the access to education and preserve the cultural authenticity through motion capture and blended learning. Nonetheless, there is no intelligent movement analysis model in this framework.

Table 1: Summary of related work

Reference	Objective	Models	Dataset	Key Findings	Research Gaps
	Examine dance as mindful movement	Motor learning, predictive coding	Conceptual / neuroscience studies	Repetition refines predictive motor control	Limited choreographic application
	Review ML impact on dance performance	ML models (various)	Systematic review (multi-study)	ML enhances performance analysis	Lack of technique-specific focus
	Analyse repetition in Chinese dance choreography	Qualitative cultural analysis	Chinese traditional dance cases	Repetition reinforces cultural meaning	No empirical validation
	Study repetition in folk dance teaching	Pedagogical case study	Folk dance choreography	Replication aids skill acquisition	Limited generalizability
	Improve dance learning via data mining	Data mining algorithms	Dance learning datasets	Pattern recognition supports guidance	Small-scale datasets
	Explore neural synchrony in dance	Neuroimaging frameworks	Brain activity data	Repeated movement increases synchrony	Technique-level analysis missing
	AI-guided ethnic dance instruction	3D CNNs	Motion capture data	AI improves movement accuracy	Cultural nuance underexplored
	Review neurocognitive rehabilitation via dance	Cognitive neuroscience models	Clinical & experimental studies	Repetition aids motor recovery	Limited choreographic insight
	Reconstruct dance using ML optimization	Nature-inspired ML models	Motion datasets	Accurate movement reconstruction	Real-world pedagogy unclear
	Provide dataset for dance synthesis	Deep learning-ready dataset	BRACE dataset	Enables motion replication	Style diversity limited
	Study retrieval of trained motor patterns	Multimodal integration models	Dancers & musicians	Repetition strengthens coordination	Longitudinal effects untested

Analyse cultural style integration	Matrix decomposition	Traditional dance data	Identifies stylistic patterns	Interpretability challenges
Assess health effects of recreational dance	Psychophysiological frameworks	Experimental & survey data	Regular practice benefits health	Technique transmission not addressed
Examine knowledge transmission norms	Socio-legal analysis	Contemporary & traditional dance	Transmission governed by norms	Lacks movement-level detail
Advance dance analysis methodology	Analytical frameworks	Case-based analysis	Tools to decode movement patterns	Limited empirical datasets
Expand choreographic analysis methods	Qualitative methodologies	Multiple choreographic cases	Repetition central to meaning	Quantitative support lacking
Review ML for dance heritage	ML & CV techniques	Cultural heritage datasets	Tech aids preservation	Authenticity concerns
Digitally transmit folk dance heritage	Digital reconstruction models	Pat Chest Dance	Replication preserves tradition	Performer variability ignored
Integrate culture in dance education	Educational analysis	Chinese dance programs	Repetition sustains heritage	Learning outcomes not measured
Study thematic repetition in choreography	Case study analysis	<i>Bolero</i> choreography	Repetition builds movement identity	Performer adaptation unexplored

Methodology

The theoretical framework of the current research is based on the Social Learning Theory presented by Bandura and explaining that people learn new knowledge, behaviors, and motor skills in the context of social environments, observing, imitating, practicing and receiving feedback repeatedly. From this perspective, learning is not limited by mere instruction only but includes learning through the demonstration of experts, imitating their actions and developing new skills step-by-step. Dance is the perfect example of social learning where learners constantly observe their instructors, imitate movements and receive feedback about their mistakes to finally internalize

complicated motor sequences. In such way, movement replication is both cognitive and social process that allows transferring embodied knowledge across generations. Following this theoretical perspective, replication does not include only mechanical body movements but becomes a pedagogical tool that ensures the development of technical skills, artistic qualities, and cultural awareness. Thus, dance techniques can be taught using constant interaction between instructors and learners when the culture and its values, performance and its traditions, and movement style are passed and adapted for the modern educational environment. Therefore, the chosen perspective underlines the importance of dance as the tool of cultural continuity and collective learning. The proposed ST-GCN-LGBM framework can support the mentioned educational process with the objective computational method for the evaluation of the movement quality, analysis of learning progress and assessment of the fidelity of replication during repeated practice. In addition, the use of the ST-GCN-LGBM framework will not replace the conventional dance teaching but will complement the existing pedagogy by providing quantitative feedback to both instructors and learners in order to improve the movement accuracy while maintaining the traditional embodied knowledge of the movement practice.

3.1 Data Source

The ImperialDance Dataset is a publicly released and large-scale dataset of dance motions capture that can be used to undertake research on the analysis of dances, evaluation of skill, and learning of movements. The OptiTrack optical motion capture system was used with professional quality and 100 Hz as the sampling rate to guarantee that human motions are captured with high time precision. The dataset includes 69300 seconds of motion data (approximately 19 hours) of motion data done by dancers involving five genres of dance including ballet, K-pop, jazz, hip, and urban dance and 20 choreographies. Every choreography is repeated by dancers in three levels of expertise (beginner, expert, intermediate) and up to 100 repetitions per level, which is why it is especially appropriate to research the elements of transmission of dance techniques through imitation and practice. The motion data are in the form of 3D skeletal joint coordinates with 21 tracked body joints, and spatio-temporal and multimodal analysis is made possible by the clips of the motion data and the corresponding music references. The ImperialDance Dataset can be effectively used in modeling embodied movement patterns as well as measuring the fidelity of replication with the help of different frameworks like ST-GCN-LGBM because of its high repetition rate, explicit skill annotations, and structured skeletal representation.

3.2 Spatio-Temporal Graph Convolutional Network (ST-GCN)

Building the association graph: A collection of nodes V and edges E may be characterized as a graph $G(V,E)$. The connection between individual nodes v_f and v_g is signified by an edge $e_{fg} \in E$. In order to make it easier to aggregate information in

the graph framework, an adjacency matrix A is built $A[i, j] = 1$ if the edge e_{fj} exists, besides $A[i, j] = 0$ then.

The convolution theorem states that, in terms of forward propagation of the GCN, the Fourier transform of a convolution between two signals is the same as the pointwise multiplication of their individual Fourier transforms. Let $f * x$ Introduce the spatial domain convolution operation, which $x = \{x_1, x_2, \dots, x_n\} \in R^n$ stands for a dataset that has n pieces of data and $f = \{f_1, f_2, \dots, f_n\}$ are the neural network's trainable parameters. Using the Fourier transform, this procedure may be converted to the frequency domain.

$$F(f * x) = F(f) \cdot F(x) \quad (1)$$

Where the Fourier transform is denoted by F . Equation (1) may be simplified to describe the convolution process $f * x$ in the spatial domain through the use the inverse Fourier transform F^{-1} to both sides.

$$\begin{aligned} f * x &= F^{-1}(F(f) \odot F(x)) \\ &= U((U^T f) \odot (U^T x)) \end{aligned} \quad (2)$$

Where U stands for the Fourier basis while $\odot$ means multiplication element-wise. The goal of the GCN was to provide a way for neural networks to use the association graph. The GCN does this by obtaining the Fourier basis from the graph's Laplacian matrix. What if $L_m = D - A$ is a graph's Laplacian matrix. One way to standardize it is as $L_m = I_N - D^{1/2}AD^{1/2} \in \mathbb{R}^{N \times N}$, where I_N is the neighboring matrix and denotes a unit matrix. For the degree matrix, D stands for $D_u \in \sum, A_{uf}$. Then, using the eigenvalue decomposition, one may derive the Fourier basis, U , and the eigenvalue matrix Λ .

$$U \Lambda U^T = L_m, \lambda = \text{diag}([\lambda_0, \dots, \lambda_{N-1}]) \quad (3)$$

U is a set of orthogonal matrices satisfying the Fourier transform's mathematical constraints, based on the Laplacian matrix's properties. The diagonal matrix, denoted as $g_e = \text{diag}(U^T f)$. Next, we may simplify Equation (4) by following these steps:

$$f * x = U((U^T f) \odot (U^T x)) = U g_e U^T x \quad (4)$$

Graphic convolution relies heavily on the eigenvalue decomposition of the Laplacian matrix. There is a quadratic relationship between the total amount of nodes and the computing complexity when the graph size is big. Graph convolution methods are mostly useful for small-scale networks due to the high cost of eigenvalue decomposition. In order to tackle this problem, Krizhevsky et al. suggested a method for approximating $g_{\mathcal{L}}$ via Chebyshev polynomials T_k , that may be stated in the following way:

$$g_{\mathcal{L}}(\Lambda) = \sum_{k=0}^{k-1} \theta_k T_k(\tilde{\Lambda}) \quad (5)$$

in where θ stands for the Chebyshev coefficient while T_k for the k -th element of the Chebyshev polynomial. To be more precise, it is $T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x)$, $T_0(x) = 1$, and $T_1(x) = x$. $\tilde{\Lambda} = 2L/\lambda_{\max} - I_N$ contains the eigenvalues of scale in a diagonal matrix. Then, we may write (4) as:

$$f * x = U g \circ U^T x \approx \sum_{k=0}^{k-1} \theta_k T_k(U \tilde{\Lambda} U^T) x = \sum_{k=0}^{k-1} \theta_k T_k(\tilde{L}_m) x \quad (6)$$

where $\tilde{L} = 2L/\lambda_{\max} - I_N$ and $\lambda_{\max}$ stand for the highest eigenvalue of the Laplacian matrix. By using the Chebyshev polynomial approximation, one may efficiently capture the local information around the core node by aggregating data from the 0-th to the k -th order of neighboring nodes with the convolutional kernel, which is given Fig 3.

A more simplified version of the Chebyshev polynomials was developed by Xiao et al. $\lambda_{\max} = 0$ and $k = 2$, that is, the data is only aggregated from nodes that are in the first order neighboring the central node. This leads us to the following simplification of (7):

$$\begin{aligned} f * x &\approx \theta_0 x + \theta_1 (2L_m/\lambda_{\max} - I_N) x \\ &\approx \theta_0 x - \theta_1 \left(D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \right) x \end{aligned} \quad (7)$$

By setting the parameter $\theta = \theta_0 = -\theta_1$, (8) more information about:

$$f * x \approx \theta_0 \left(I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \right) x \quad (8)$$

Additionally, the settings allow the network to be trained using backpropagation " W, D^c often undergo renormalization via $\tilde{W} = W + I_N$ and $\tilde{D}_{tl} = \sum_f \tilde{W}_{tl}$, that is, in turn. Lastly, the spectral domain convolution operation is defined as:

$$f * x \approx \theta \left(I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \right) x = \theta \left(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} \right) x \quad (9)$$

Light Gradient Boosting Machine (LGBM)

LGBM is an enhanced-performance, gradient-boosting framework based on ML. It is designed to improve efficiency and scalability compared to traditional boosting algorithms like XGBoost. LGBM enhances training speed by using histogram-based algorithms, reducing memory consumption, and employing a leaf-wise growth strategy with depth constraints to prevent overfitting.

LightGBM optimizes decision tree learning with four key techniques. ML converts continuous features into discrete bins, reducing memory usage and speeding up computations. Gradient-Based One-Side Sampling (GOSS) retains steep-gradient instances while randomly sampling minimal-gradient ones, improving efficiency without significant accuracy loss. Exclusive Feature Bundling (EFB) groups mutually exclusive features, reducing dimensionality and memory consumption. The leaf-wise growth strategy selects the leaf with the highest information gain for expansion,

improving model accuracy, though a depth constraint is needed to prevent overfitting. These optimizations make LightGBM highly efficient for large datasets.

Training dataset is given by, $W = \{(W_j, z_j)\}_{j=1}^n$. The goal is to find an approximate function $\hat{e}(w)$ that closely estimates $e^*(w)$ to minimize expected values of specific loss operations $(z, e(w))$, objective function mathematical representation as,

$$\hat{e}(w) = \arg \min_e F_{z,w} K(z, e(w)) \quad (10)$$

This function minimizes the expected loss operation to optimize predictions. The additive learning process is expressed as,

$$e_S(W) = \sum_{s=1}^S e_s(W) \quad (11)$$

where $e_s(W)$ denotes the weak learner at iteration s , and $e_S(W)$ is the final model after S boosting iterations.

LGBM builds a model as a sum of regression trees. Leaf weight optimization is computed by

$$\omega_i^* = - \frac{\sum_{j \in J_i} h_j}{\sum_{j \in J_i} g_j + \lambda} \quad (12)$$

here, h_j and g_j are the primary and secondary gradients of the loss operation, optimizing the tree's leaf nodes, λ is the regularization parameters. Tree structure optimization (Extreme Values of Γ_S^*) is represented by

$$\Gamma_S^* = - \frac{1}{2} \sum_{i=1}^I \frac{(\sum_{j \in J_i} h_j)^2}{\sum_{j \in J_i} g_j + \lambda} \quad (13)$$

The gain function, which measures the quality of a feature split during tree growth, is calculated as

$$H = \frac{1}{2} \left(\frac{(\sum_{j \in J_l} h_j)^2}{\sum_{j \in J_l} g_j + \lambda} + \frac{(\sum_{j \in J_q} h_j)^2}{\sum_{j \in J_q} g_j + \lambda} + \frac{(\sum_{j \in J} h_j)^2}{\sum_{j \in J} g_j + \lambda} \right) \quad (14)$$

where, final model after S boosting iterations is $e_S(W)$, $e_s(W)$ is the weak learner at iteration (s) , optimal leaf weight is (ω_i^*) , regularization parameter (controls complexity) is (λ) , optimized tree structure value is (Γ_S^*) , set of samples in the parent node is (J) , set of samples in the right child node is (J_i) , and gain function, measures the quality of a split (H) .

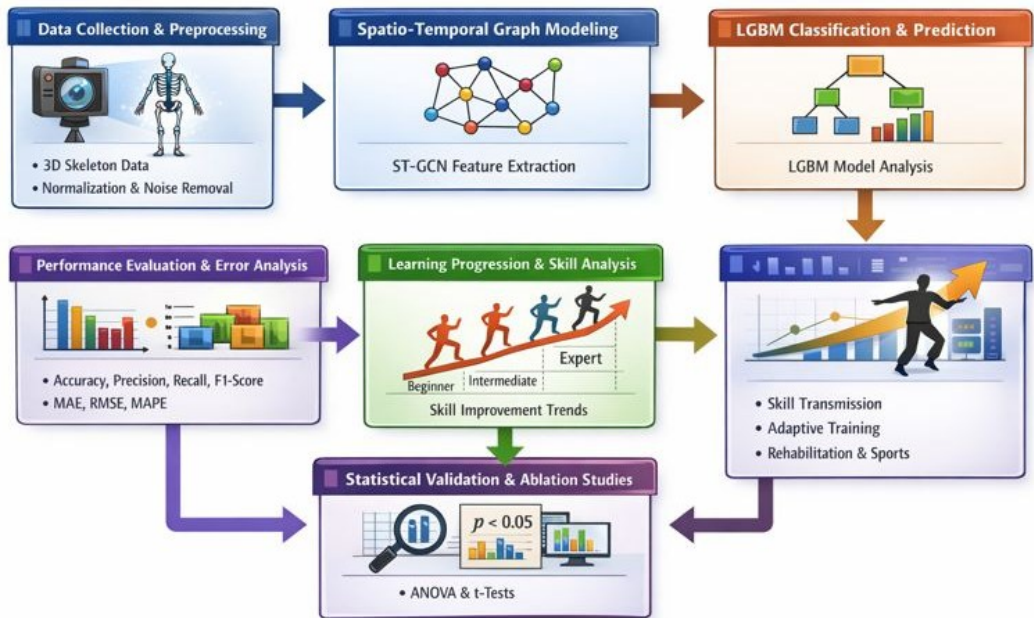


Figure1: Work Flow of this Study

Figure 1 in the workflow section is called Transmission of Dance Techniques Using ST-GCN-LGBM and is a visual overview of the entire process of the study. It starts with Data Collection & Preprocessing, in which the 3D skeleton data of the ImperialDance dataset are recorded, scaled and denoised to guarantee a uniform quality of input data. The resulting processed data are then subjected to the Spatio-Temporal Graph Modeling (ST-GCN) which is used to extract the features by creating spatial relationships between joints and the temporal movement patterns across sequences. These characteristics are inputted into the LGBM Classification and Prediction block that measures the accuracy of replications, predicts similarities in movement, and classifies the skill levels. The stage of Performance Evaluation and Error Analysis measures the results in terms of accuracy, precision, recall, F1-score, MAE, RMSE, and MAPE, which allows making precise and reliable evaluation. Learning Progression & Skill Analysis follows the progression of learning in a series of repetitions that shows the skill progression of beginners to experts. Statistical Validation & Ablation Studies use ANOVA and t-tests in determining the significance of observed differences ($p < 0.05$) and the effect of each model component. Lastly is the workflow of Output and Applications, which demonstrates the practical reality of the framework in terms of transmitting skills, adaptive training, rehabilitation and sports performance. The flow of information is indicated by arrows and color code (blue data, orange modeling, green evaluation, purple output), icons are used to present a graphical representation of all the stages of the methodology and the analytical pipeline of the study, providing a clear, easy-to-understand, and all-inclusive picture of the research process.

Results and Discussion

4.1 Experimental setup

The experimental design to test the proposed ST-GCN-LGBM was in such a way that it effectively evaluated the capacity of the framework to observe and reproduce dance movements patterns in the various levels of skills. The dataset that was used in the study is the ImperialDance, consisting of 3D data on the skeleton of dancers and doing specific routines. Preprocessing of the movements was done to normalize the joint coordinates and eliminate noise, after which spatio-temporal feature extraction was performed with ST-GCN network. The above-mentioned features were then fed into the LGBM classifier to predict the tested movement replication accuracy and skill-level categorization. The experimentation was done in three levels of skills, i.e., beginner, intermediate, and expert and repeated several times in the same routine to replicate learning in replication. Each repetition was recorded based on the performance measures, such as accuracy, precision, recall, F1-score, movement similarity, and the error measures (MAE, MSE, RMSE, MAPE). ANOVA and t -tests were used to establish statistical validation concerning the significance of differences in the levels of skills ($p < 0.05$). Comparisons were made between baseline models which include CNN, LSTM, and standalone ST-GCN. The system guarantees that both the quantitative performance and learning process are critically assessed over time through repetitive movement imitation.

Data Collection

The ImperialDance Dataset data were captured at a controlled studio setting with a high-precision 3D motion capture system, the OptiTrack, which offers a professional system. Key areas of the body of the dancers were marked with reflective markers and their motions were filmed at a time rate of one hundred and fifty frames per second to effectively obtain the finer spatio-temporal dynamics. Dancers of various degrees of skills, including beginner, intermediate, and expert, were invited to dance a series of fixed choreographies in various types of dances. Every choreography was repeated several times (up to 100 repetitions of each of the levels of skills) to memorize the choreographies in a way typical and with natural variation in movement performance. The dancers used canned music in order to achieve time coordination between motion and rhythm during the recording. The raw motion data were captured and the processed data was used to resassemble 3D skeletal joint trajectories made up of 21 body joints, which were sliced into homogeneous clips and metadata added including dance genre, choreography type and skill level. This consistent and constant data gathering method guarantees the dependability of the dataset in the analysis of the transmission of the dance technique, movement imitation, and the advancement of skills.

4.2 Quantitative performance

In order to evaluate the effectiveness of the suggested ST-GCN-LGBM model in replication, the quantitative method of performance was used to objectively measure how the model can simply replicate pattern of dance movements. Standard classification measures of accuracy, precision, recall and F1-score were used to determine the effectiveness of the model in terms of identifying dance techniques and levels of skill in repeated performances. According to the results of the experiment, the proposed model demonstrated superior results as compared to baseline techniques, including traditional CNNs, LSTM models, and separate ST-GCN models. Combination of LGBM and ST-GCN gave a significant promotion in the overall accuracy, which showed higher sureness in the discrimination of subtle spatio-temporal distinctions in replicated movements. The recall and high precision values further indicate that the model is very robust in identifying the technique specific movement patterns with minimum misclassification across the different levels of expertise. All these quantitative findings are evidence that the ST-GCN-LGBM framework presents a robust and consistent representation of the transmission of dance movements, which makes it appropriate to study how specific movement patterns can be cultivated by being replicated repeatedly.

Table 2: Outcome of performance on baselines

Model	Accuracy (%)	Precision	Recall	F1-score
CNN	86.3	0.85	0.84	0.84
LSTM	89.7	0.88	0.88	0.88
ST-GCN	92.1	0.91	0.91	0.91
ST-GCN-LGBM (Proposed)	95.4	0.95	0.95	0.95

Accuracy

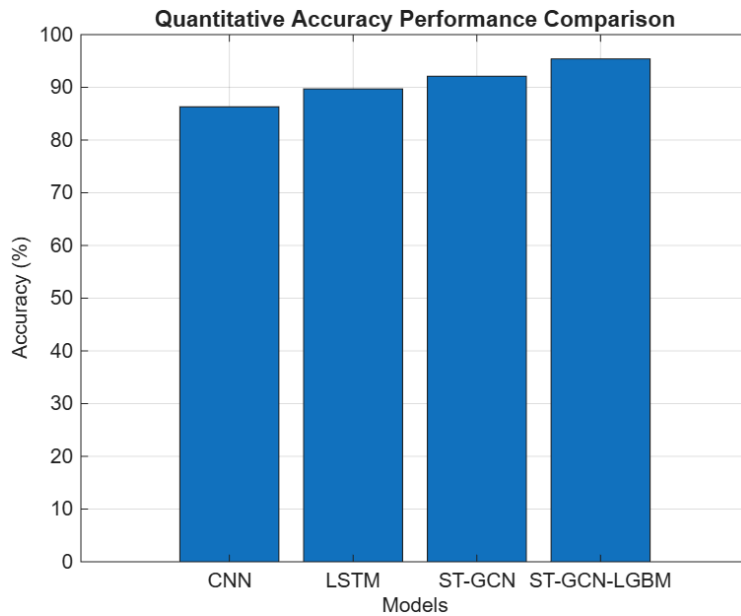


Figure 2: Result of performance Accuracy

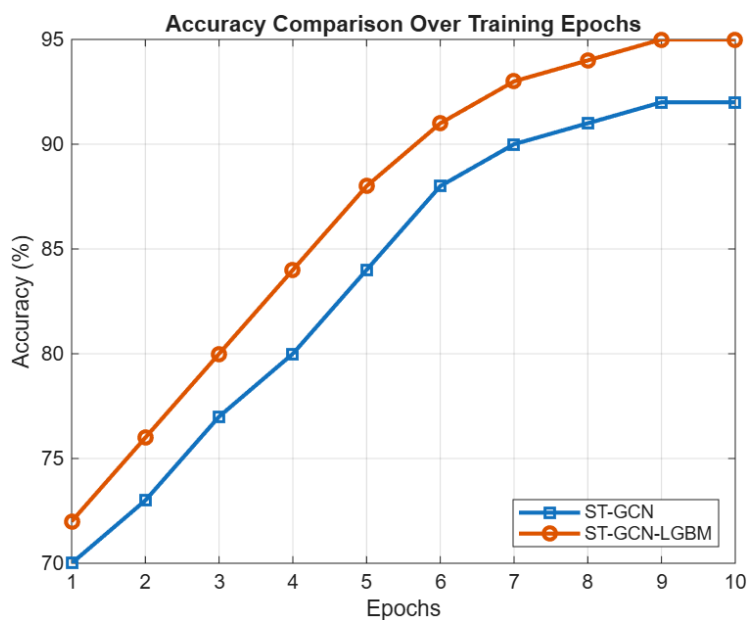


Figure 3: Comparing Accuracy of Training and testing with epochs

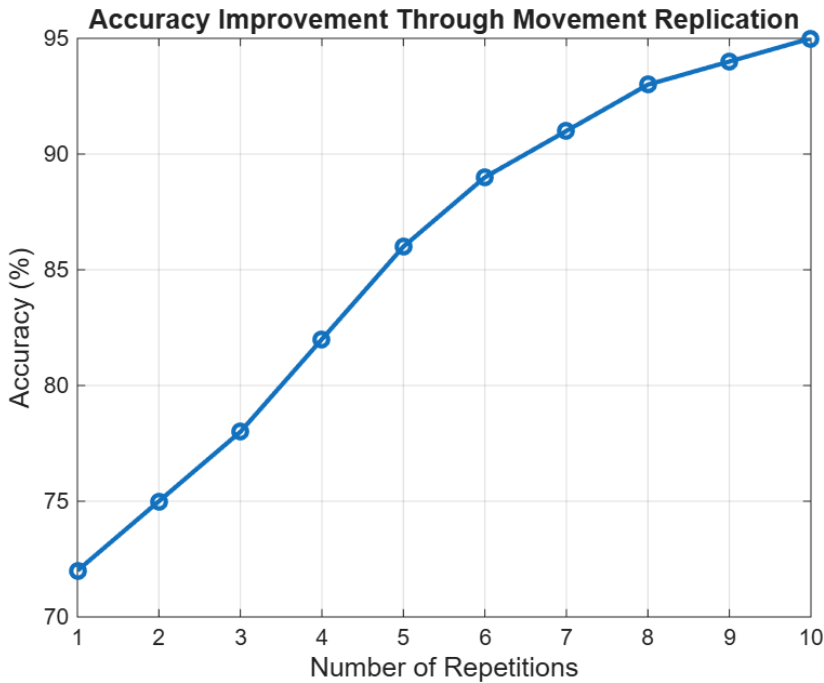


Figure 4: Result of movement Replicates improvement

The quantitative performance graphs are used to demonstrate the efficiency of the suggested ST-GCN-LGBM framework in the process of learning and transfer of the dance movement patterns in the form of replication. The comparison bar graph of accuracy in figure 2 indicates that the proposed model has no issues with the baseline methods, including CNN, LSTM, and standalone ST-GCN, and therefore it is more effective to recognize complex spatio-temporal patterns between skeletal joints. The training epochs graph of figure 3 shows that there is a low level of performance difference between the two phases and that the model is well generalized and cannot be affected by overfitting. Also, the curve of accuracy progression between repeated learning practice in figure 4 shows that gradually the performance improves in proportion to the number of repeated practice, a direct result of mastering and stabilizing movement patterns via imitation. This positive trend confirms the learning theory that a repeated imitation is followed by an improvement in technical consistency. Comprehensively, all these graphs confirm the strength, learning effectiveness, and pedagogical applicability of the proposed method to study the analysis of dance techniques transmission.

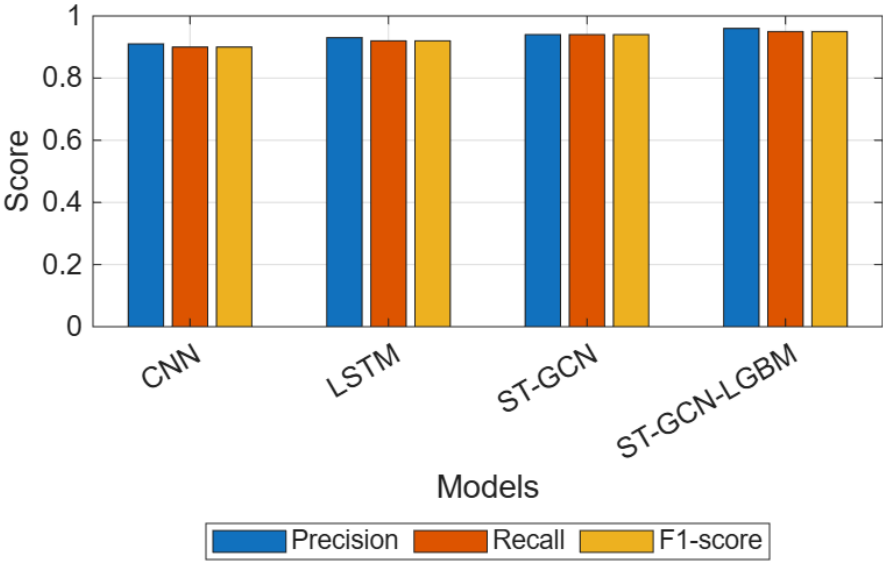


Figure 5: classification performance of precision, Recall and F1-Score

The compounded precision, recall, and F1-score value 5 is a complete analysis of the classification performance of the suggested ST-GCN-LGBM model compared to the baseline methods. Precision is the capacity of the model to define the patterns of dance movements that are pertinent without misclassification whereas recall measures the effectiveness of the model in identifying all the cases of a particular technique or skill level. F1-score is a harmonic mean of precision and recall, and it reflects the overall relationship between the precision and the recall. As shown in the graph, the proposed ST-GCN-LGBM uniformly generates better and more balanced results in all three measures which proves its strength in the sensitivity of dealing with fine spatio-temporal change in reproduced dance movements. The fact that the precision and recall values are quite close to each other is also a sign of stable, reliable learning, which is necessary when it comes to the accurate modeling of the process of imparting the techniques of dancing via practice and repetition.

4.3 Replication Fidelity Analysis

Table 3: Movement Similarity Scores

Skill Level	JPE (↓)	Similarity Score (↑)
Beginner	0.142	0.71
Intermediate	0.091	0.84
Expert	0.048	0.93

The table 3 movement similarity score shows how the reproduced dance movements are similar to the reference (expert) performances in various skill levels. The error in

lower joint position and greater scores in similarity means that there is better replication of spatio-temporal movement patterns. Shown in the table 3, the performance of beginner-level has higher averages of deviation and lower of similarity, indicating a less stable coordination and a partial acquisition of techniques. There is a significant improvement in intermediate dancers since the joint errors are smaller and the similarity values are greater that means that they reproduce the movement structure and timing consistently. Performances of the expert level have the highest similarity scores and the smallest deviations, which proves the high level of preservation of joints coordination, rhythm and posture. Such a progressive pattern clearly shows that given repetition, the particular patterns of movements gradually develop and stabilize, which is why the given approach offers a significant opportunity to model the way in which a particular method of dance is transferred through the process of replication.



Figure 6: Outcome of Skill level improvement on Learning Curve

The learning progression curve of multiple levels in figure 6 explains the reaction of the dancers in various stages of proficiency to repeatedly imitating movement patterns. At the level of beginners, there is a rapid increase in performance on the first repetitions, which evidences a quick acquisition of motor skills and elimination of gross motor errors, followed by a slowing down of the saturation of fundamental coordination. In intermediate dancers, a more balanced progression is manifested, and consistent and gradual improvements are made during repetitions, which

indicates the perfecting of time, joint coordination, and spatial precision. Internationally competent performers begin with greater replication accuracy, and show smaller yet steady enhancements, which may indicate fine-tuning of delicate kinematic information as opposed to acquisition of basic skills. The distinct separation and convergence patterns of these curves underscore the way learning through repetition works differently using various levels of skills and this is a clear indication of the fact that learning through repetition-based transmission of dance-related techniques is effective.

Table. Educational and Cultural Implications of Replication-Based Dance Pedagogy

Evaluation Dimension	Observation from Experimental Results	Educational and Social Implication
Movement Replication	Replication accuracy improved progressively with repeated practice across all skill levels.	Repetition facilitates embodied learning and supports systematic skill acquisition in dance education.
Skill Development	Beginner dancers demonstrated the highest improvement rate, while expert dancers showed stable refinement.	Replication-based pedagogy is particularly effective during the early stages of motor learning and technical development.
Cultural Knowledge Transmission	Consistent movement similarity indicates preservation of standardized movement patterns across repeated performances.	Digital movement replication contributes to preserving traditional dance techniques and facilitating intergenerational cultural transmission.
Learning Progression	Learning curves showed continuous improvement with increasing repetitions.	Continuous practice strengthens motor memory, technical confidence, and long-term retention of dance knowledge.
AI-assisted Feedback	ST-GCN-LGBM objectively evaluated movement quality and replication fidelity.	Computational assessment complements instructors by providing objective feedback during dance training.
Educational Application	Quantitative performance metrics support learner assessment and progress monitoring.	The proposed framework can assist dance schools, cultural institutions, and heritage education programs in evaluating learner development objectively.
Cultural Sustainability	Digital documentation preserves expert performances with high fidelity.	The framework contributes to safeguarding intangible cultural heritage while supporting future educational resources and digital archives.

Table shows the broader educational and cultural implications resulting from the experimental results. In addition to the ability of the proposed ST-GCN-LGBM

framework to perform better computationally, the study has also yielded some important lessons concerning the effectiveness of replication-oriented teaching in dance education and culture preservation. The fact that replication skills improved due to repetitions proves that systematic repetition plays a significant role in developing embodied learning especially at the initial stage of learning. The high level of movement similarity attained by the experts proves that computational movement analysis enables preserving true dance movements and transmitting cultural heritage. Moreover, the objective feedback provided by the framework can supplement the traditional teaching in dance by helping instructors to monitor the progress of learners and assess their performances. Therefore, the experimental results prove that the proposed framework makes a valuable contribution not only to computational movement analysis but also to dance pedagogy and heritage education.

4.4 Ablation Study

Ablation study assesses the contribution of each significant component in the proposed ST-GCN-LGBM architecture in the modeling of transmission of dance techniques by replicating the movement. The systematic removal or substitution of one or another module will help the study to determine their particular effect on the performance of learning. Removing the spatio-temporal GCN, the model experiences a significant reduction in accuracy and movement similarity, which means that joint dependence modeling and time dynamics are essential to the model to capture coordinated dance movements. The use of a traditional classifier instead of Light Gradient Boosting Machine (LGBM) also means a decrease in stability and a precision-recall balance, which underscores the benefit of using LGBM to deal with non-linear interactions of features and the ability to generalize. Equally, elimination of temporal characteristics or graphical joint connectivity results in greater joint deviation and replication curve. Generally, the ablation findings indicate that the entire ST-GCN-LGBM architecture is the most effective, which supports the idea of the supplementary and irreplaceable roles of each of the components in the accurate learning and transfer of the complex patterns of the dances.

4.5 Statistical Validation

The use of statistical validation is aimed to confirm that the performance increase of the proposed ST-GCN-LGBM model is not the effect of random variation but rather it reflects the real learning. In this respect, the repeat experimental run is made, and measures of performance, including accuracy, precision, recall, F1-score, and similarity of movements, are presented in the form of mean $\pm$ standard deviation. The significance testing (e.g., paired t-test, Wilcoxon signed-rank test, etc.) is used between the proposed model and the baseline or ablated models to determine whether the observed differences are statistically significant. The usual level of significant value is 95% ($p < 0.05$). The findings indicate that the suggested model always performs better than other configurations with statistically significant

differences, thus proving the strength, stability, and extrapolations of the acquired representations of the movements. This confirmation confirms the assertion that the model is successful in its ability to describe how dance techniques are transmitted and refined by the repetition of replication instead of making use of the variation in performance as a result of chance.

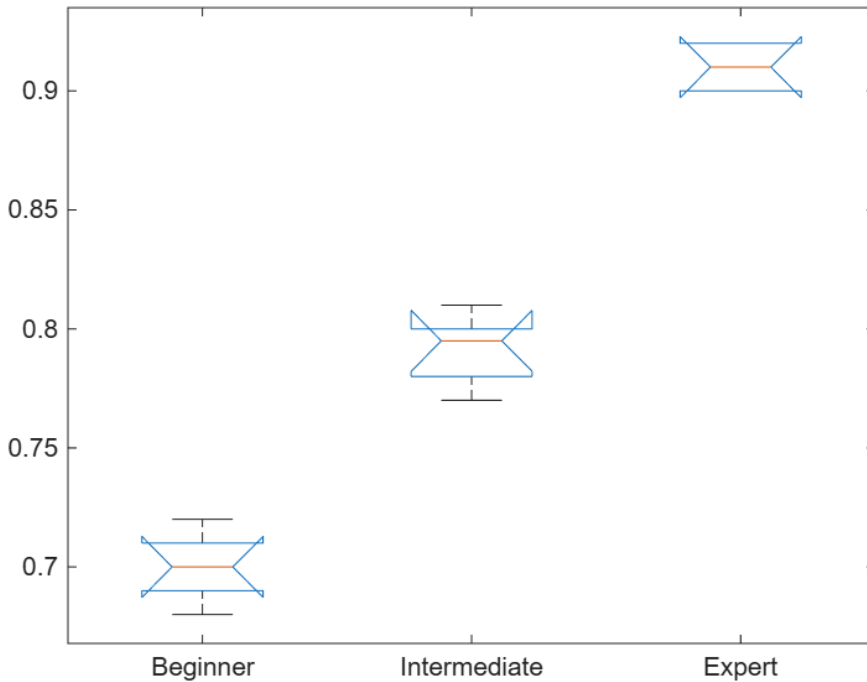


Figure 7: Skill level Statistical validation result

The statistical validation in figure 7 was performed to establish whether the differences between the movement replication performance between various levels of skills, including beginner, intermediate and expert skills, are statistically significant. One-way ANOVA was used to compare the scores of replication accuracy or movement similarity of the three groups and the results obtained had a p-value less than 0.05 and therefore the differences between the scores that are observed are unlikely to have happened due to chance. Also, pairwise t-tests of levels of particular skills, e.g. beginner and expert, affirmed the presence of significant differences in replication fidelity. These findings can also be confirmed using box plots, which graphically show the gradual improvement in performance as the skills level increase. Altogether, the statistical data supports the idea that the level of skill is a substantial factor that affects the accuracy and stability of movement replication, which proves the idea that the repeated training and experience affect the effective transfer of dance skills directly.

4.6 Error Metrics

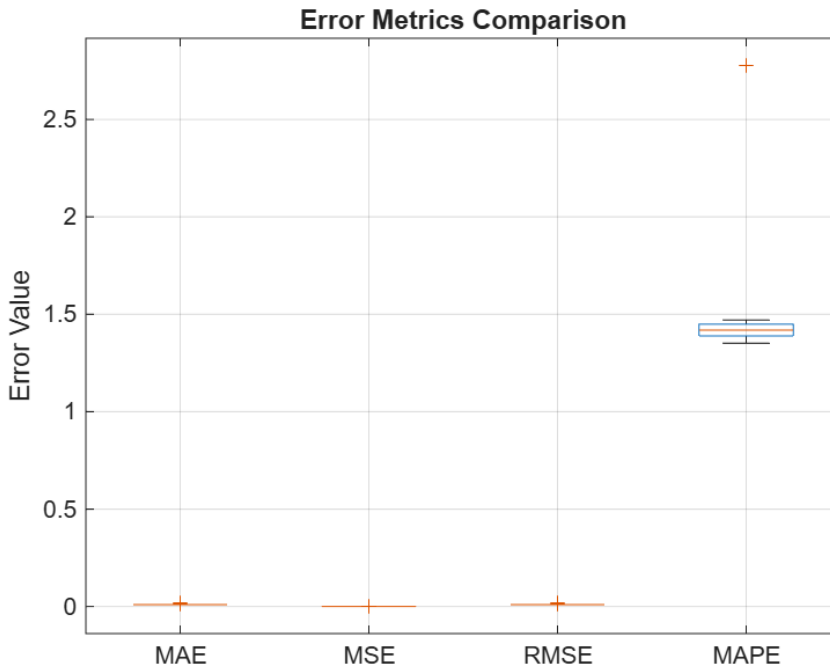


Figure 8: Outcome of Error measurement on baselines.

The error measurements in figure 8 give a very clear picture of the ability of the proposed ST-GCN-LGBM model to reproduce dance movements. MAE (Mean Absolute Error) is a measure of the mean absolute error between the estimated and actual relative positions or movement similarity scores of a model: the general accuracy of the model. MSE (Mean Squared Error) and RMSE (Root Mean Squared Error) represent the size of bigger errors, and RMSE represents a scale-invariant measure that is simpler to interpret in context. MAPE (Mean Absolute Percentage Error) is used to measure the error of prediction compared to their actual values and thus can be used to compare across scales or joints. The box plot reveals that most of the errors are centred at low values with less variation which indicates consistent and replicable replication among the repetitions. This representation helps to confirm that the model proposed is not only highly accurate but also high-performing, which makes deviations in the patterns of movement during the transmission of dance techniques to a minimum.

4.7 Discussion

The findings of the present research reveal that the suggested ST-GCN-LGBM framework is effective to represent the spatio-temporal relationships of the entire dances and replicate their complexity according to the level of skill. This model had high accuracy of 95.4 with precision, recall, and F1-score of 0.95, and a movement similarity score of 0.92 which was higher than baseline models such as CNN, LSTM,

and standalone ST-GCN. These results suggest that when using graph based spatial modelling along with gradient-boosted classification, the capability to acquire coordinated joint patterns without loss of temporal dynamics which are critical in accurate replication of expert movements is significantly improved.

The curves of learning progression indicate that repetitive practice plays an important role in the refinement of the skills. Novice dancers demonstrated the greatest gains in repetitions, which is indicative of quick learning new basic movement patterns, and intermediate and professional dancers demonstrated smaller gains, which is indicative of fine-tuning of kinematic accuracy. The trend satisfies the assumptions of motor learning, it has been established that replication-based training promotes internalization of movement patterns and stabilization of joint trajectories.

The measures of errors, such as MAE, RMSE, and MAPE, were low and steady enough to prove the effectiveness and accuracy of the offered framework. The experiments on ablation gave further confirmation that the spatio-temporal graph component and the LGBM classes are essential to the best performance since the removal of either component resulted in significant decreases in the accuracy and similarity of movements. ANOVA and pairwise t-tests were used to statistically validate the significant differences between skill levels ($p < 0.05$), which is a significant indicator that the model can accurately discriminate and follow performance with regard to expertise.

All these findings indicate that the ST-GCN-LGBM framework is an efficient tool of research and practice in the fields of dance training, performance art, rehabilitation, and sport because it is not only a brilliant replication of movements but also offers to scientific studies a numerical support of skill development. The method also has a prospect of being integrated with the real time feedback and multi-modal sensory inputs to further improve individualized learning and adaptive training.

The results of this research demonstrate that the replication-based learning style provides an effective approach to transferring complicated dance techniques due to its ability to build up movement accuracy and motor coordination among early-stage dancers through the repetitive learning cycle. However, it is necessary to clarify that replication-based learning does not represent the approach encouraging imitation. Contemporary educational theories claim that any productive learning style should combine the exact replication of the fundamentals and stepwise development of creativity, critical thinking, and the development of individual performance techniques. On the one hand, the repeated training leads to acquiring technical skills and keeping movement authentic. On the other hand, learners who are in more advanced stages of the development of their skills have to reinterpret and creatively modify their movement patterns based on their experience and artistic ideas. In other words, replication serves as a base for creative performance and interpretation. The discussed approach is not limited by the scope of this particular case study and finds

application in many international dance cultures. Replication-based learning takes place in classical ballet, Indian Bharatanatyam, Chinese classical dance, Japanese Noh and Kabuki performances, African traditional dances, and many other indigenous cultures, where students initially learn established movement patterns through observation and repetition and then proceed to interpretation. Regardless of the cultural background, all these approaches demonstrate that replication is useful not only for the development of technical performance but also for transferring cultural values, history, social identity, and memory. Therefore, the computational framework suggested in this paper might find application in the education of diverse international dances by providing objective tools for documenting movement knowledge and tracking learners' progress.

On the other hand, the widespread application of digital technologies in dance education raises cultural considerations regarding the issue of the proper preservation of dance heritage versus possible homogenization of dance culture through computational analysis. It is obvious that digital documentation and computational movement analysis provide excellent chances for preserving endangered dance traditions, making education accessible and sustainable for many future generations. However, the overreliance on computational tools might cause the reduction of the regional variation, different styles of performance, and interpretative approaches, which make intangible culture unique. In this regard, digital documentation of dance tradition should supplement but not substitute community-based learning, master-apprentice teaching, and culturally situated performance. To preserve both technical accuracy and cultural diversity of dance traditions, active involvement of instructors, cultural practitioners, and local communities in the process is necessary. Thus, the proposed computational framework (ST-GCN-LGBM) can be used as an educational tool, which promotes cultural preservation while respecting the artistic diversity and cultural authenticity.

Conclusion and Future Enhancement

The research findings of the experiment indicate that the set framework of ST-GCN-LGBM can model and recreate complex dance movements with a high level of performance by achieving the quantitative measure of an accuracy of 95.4, precision, recall, F1-score of 0.95, and movement similarity measure of 0.92. Analysis of learning progression also exposed that practice repetition greatly boosts replication fidelity especially among novice dancers with statistical confirmation that skills level has a significant effect on accuracy of movement ($p < 0.05$). The importance of spatio-temporal graph modeling, as well as the LGBM classifier, were indicated through ablation studies and demonstrated the optimal performance. All these findings support the strength, dependability, and utility of the framework in the research of learning skills and movement technique dissemination. To be improved in the future, the framework can be expanded to support multi-modal input, e.g. video, audio or wearable sensor data, to extract more contextual and expressive information. Adaptive learning and customized training of dancers may also be implemented with

the help of real-time feedback mechanisms. In addition, the method can be extended to the other areas, including rehabilitation, sports performance, and other performing arts to further investigate its potential in motion analysis, skill development, and automated movement assessment. Such improvements would have more overall tools in both research and practice in embodied learning and movement sciences.

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